Chapter 73
Intelligent Approaches for Vibration Fault Diagnosis of Steam Turbine-Generator Sets

Yann-Chang Huang, Chien-Yuan Liu and Chao-Ming Huang

Abstract To enhance diagnosis accuracy of vibration faults for steam turbine-generator sets (STGS), this paper presents evolutionary programming-based radial basis function (EP-RBF) networks. The proposed EP automatically determine the optimal parameters for the RBF network, which includes the number of neurons in the hidden layer, the centers of hidden neurons, the spread parameters, and the weights in the output layer of the RBF network. The test results demonstrate that the proposed EP-RBF network has a higher diagnostic accuracy than the RBF network and multilayer perceptron (MLP) network trained by error back-propagation algorithm. Moreover, this paper reveals that the proposed EP-RBF network can apply to effectively diagnose vibration fault of STGS.

Keywords Intelligent approaches · Fault diagnosis · Steam turbine-generator sets

73.1 Introduction

Artificial intelligence (AI)-based methods have been used to diagnose vibration faults of STGS, which include expert systems, fuzzy logic systems, and artificial neural networks (ANNs). The expert systems [1, 2] combined an inference engine

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with a range of knowledge to develop guidelines for fault diagnosis of STGS; however, design an efficient inference engine to draw conclusions from a large body of rule-based knowledge is difficult, and the inference processes are time-consuming.

Fuzzy logic systems [3, 4] were expressed in imprecise linguistic terms; they have been developed to solve vibration fault problems with uncertain and inaccurate information. However, like an expert system, a fuzzy system depends heavily on the operators' experience to determine the fuzzy inference rules and their associated membership functions. Therefore, practical vibration fault data collected from a machine may not be applied to solve the diagnosis problems.

The ANNs [5, 6] captured complex input–output relations with well interpolated and extrapolated capabilities; they provided real-time response in practical applications. Although ANNs have been successfully applied to diagnose vibration faults of STGS, some problems remain unsolved, including the local and slow convergence during training, and determining network structure and parameters.

Support vector machines (SVMs) adopted the best hyperplane to extract the feature from linear or nonlinear data [7, 8]; however, determining a best hyperplane in SVM is often difficult and depends strongly on the operators' experience or trial-and-error experiments. Moreover, to enhance the effectiveness of PSO [9] in designing the optimal SVM model, an enhanced PSO algorithm was presented to increase the diagnosis accuracy of fault in STGS [8]. In comparison with MLP network trained by error back-propagation algorithm, the RBF network [10] had a more compact topology and requires less training time. However, the performance for such a simple mechanism to deal with complex vibration fault diagnosis problems in a STGS must be further evaluated.

73.2 The Intelligent Approaches

Vibration signals are often used to evaluate the operating status of the STGS. Mechanical vibration of the STGS is caused by misalignment of the rotor, rotor unbalance, loose bearings, rubbing, oil whirl, and steam whirl. In this paper, signals associated with mechanical vibration were used as basic data to train the EP-RBF network. Then, the trained network was adopted to diagnose faults in a STGS. Figure 73.1 presents the structure of the intelligent approaches that describes as follows.

73.2.1 The RBF Network

An RBF network is similar to multilayer perceptron (MLP) network with three layers (input, hidden layer, and output) [11]. The major difference between the RBF network and the MLP network is that an RBF network does not use raw input

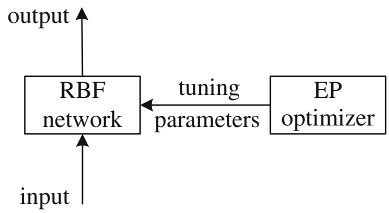

Fig. 73.1 The structure of the proposed intelligent approaches

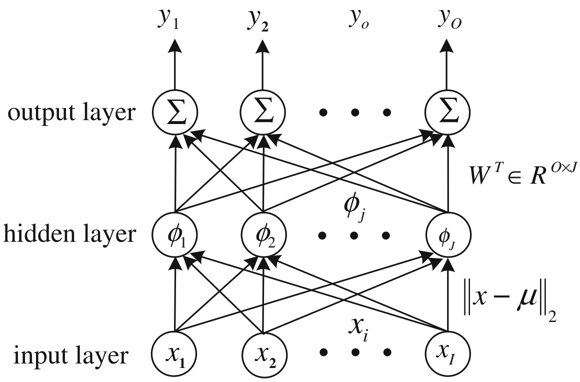

Fig. 73.2 The structure of the RBF network

data, but rather passes a distance measure from the inputs to the hidden layer. This distance is measured from some center value in the range of the variables to a given input value about a Gaussian function. The number of input nodes depends on the dimensionality of the input vector; that of hidden nodes equals the number of basis functions used in the network; that of output nodes equals the number of distinct classes.

Figure 73.2 shows the structure of the RBF network. The input and output layers of the RBF network are presented with training pairs, each consisting of a vector from an input space and a desired network output. The error between the actual and desired output is minimized according to the supervised learning algorithm and optimization criterions. As shown in Fig. 73.2, the *o*th output node of the RBF network can be described as

$$y_o = \sum_{j=1}^{J} \varphi_j\left(\left\|x - \mu_j\right\|_2\right) \times w_{oj}, = 1, 2, \ldots, O \tag{73.1}$$

where $x \in R^{I\times 1}$ is an input vector, $\mu_j \in R^{J\times 1}$ are the RBF network centers in the input vector space, $\|\bullet\|_2$ denotes the Euclidean norm, $\varphi_j(x) = \exp(-x^2/\sigma^2)$ is the Gaussian function of the *j*th center with spread parameter σ, and $w_{oj} \in R^{O\times J}$ are the weights between hidden and output layers.

Four sets of parameters govern the mapping properties of the RBF network: the number of hidden nodes, the centers of hidden neurons, the spread parameters, and the weights in the output layer. A sufficient number of centers are randomly chosen

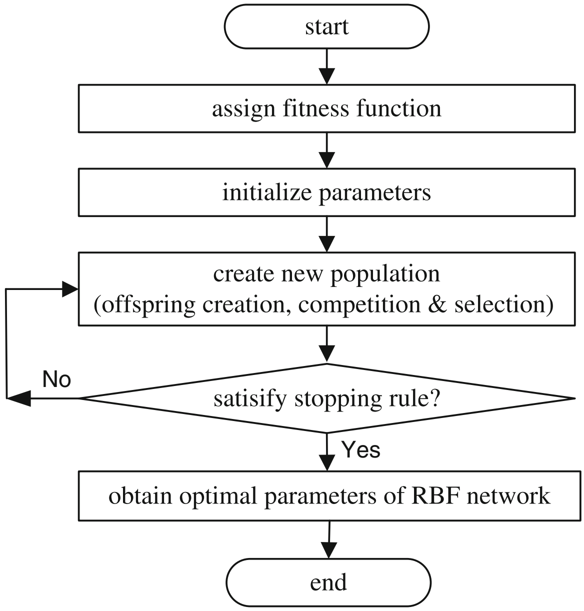

Fig. 73.3 Flowchart of the evolutionary programming algorithm

as a subset of the input space according to the probability density function of the training data. Then the gradient approach is used to tune the weights in the output layer. The disadvantage of this method is that it is prone to fall into the local minimum. Therefore, the EP algorithm was adopted to tune the parameters.

73.2.2 The EP Algorithm

The proposed evolutionary programming [12] determine the optimal parameters for the RBF network, which includes the number of neurons in the hidden layer, the centers of hidden neurons, the spread parameters, and the weights in the output layer of the RBF network. Figure 73.3 presents flowchart of the evolutionary programming algorithm. The proposed evolutionary programming with global search ability can simultaneously determine the optimal parameters for the RBF network, while avoiding the limitation of the gradient-descent technique.

73.3 Results and Discussion

This paper presented the fault vibration signals to identify the faults in a STGS using the EP-RBF network. A total of 90 samples, as shown in Table 73.1, collected from [8] was used to train and test the diagnosis accuracies of the proposed approach. Each sample contains eight input features and one fault class. The eight

Table 73.1 The 90 test dada for vibration fault of STGS

No.	Frequency bands (B)								Fault type
	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	
1	0.01	0.02	0.01	0.03	0.42	0.55	0.08	0	Misalignment
…	…	…	…	…	…	…	…	…	
15	0.02	0	0.02	0.01	0.39	0.58	0.12	0.04	
16	0.01	0.04	0.02	0.05	0.7	0.17	0.22	0.1	Unbalance
…	…	…	…	…	…	…	…	…	
30	0.05	0.03	0.03	0.06	0.85	0.25	0.27	0.13	
31	0.93	0.01	0.02	0	0.05	0.07	0	0.15	Looseness
…	…	…	…	…	…	…	…	…	
45	0.87	0.05	0.04	0.01	0.08	0.02	0.03	0.2	
46	0.08	0	0.05	0.18	0.29	0.12	0.13	0.19	Rubbing
…	…	…	…	…	…	…	…	…	
60	0.17	0.2	0.09	0.15	0.32	0.18	0.23	0.17	
61	0.06	0.91	0.12	0.08	0.18	0.01	0.03	0.14	Oil whirl
…	…	…	…	…	…	…	…	…	
75	0.02	0.69	0.1	0.09	0.15	0.01	0.02	0.12	
76	0.08	0.06	0.1	0.47	0.08	0.35	0.23	0.08	Steam whirl
…	…	…	…	…	…	…	…	…	
90	0.12	0.06	0.09	0.42	0.19	0.39	0.28	0.1	

input features represent the vibration amplitudes of different frequency bands: $<0.4f$, 0.4–0.49f, 0.5f, 0.51–0.99f, f, 2f, 3–5f, and $>5f$, which expressed by an input vector $B = [b_1, b_2, \ldots, b_8]$. The six typical mechanical vibration faults are misalignment, unbalance, looseness, rubbing, oil whirl, and steam whirl. To verify the diagnosis accuracy of the EP-RBF network, the performance was compared with that of the RBF and the MLP network methods, using the same database.

In the test cases, all of the parameters for the MLP and the RBF networks were determined by experience or by trial-and-error experiments. For the MLP network, 10 neurons were selected in the hidden layer; learning rate was set to 0.01 for training by a steepest-descent gradient algorithm. The spread parameter of the RBF network was set to 0.5; 10 neurons were chosen in the hidden layer. For the RBF and the EP-RBF networks, the maximum number of iterations was set to 5,000; the goal was set to 10^{-5}.

The diagnostic accuracies of the MLP, the RBF, and the proposed EP-RBF networks with different training and testing samples are compared in Table 73.2. The results indicate that these methods obtained 100 % accuracy for historical training data. For all models, the test accuracies were improved with increasing training samples, and the ratio of training to testing samples with 2:1 obtained the best diagnosis accuracy. The proposed EP-RBF achieved 93.33 % accuracy and outperformed the RBF and the MLP networks. Moreover, the best spread parameter of the EP-RBF network was 0.45, and the best number of neuron in hidden layer was 15. The average time ratio required to construct the diagnostic models for the MLP, the RBF, and the EP-RBF networks was 1:0.06:1.51. The

Table 73.2 Diagnosis accuracy of different models

Network	Ratio of training to testing samples	Training accuracy (%)	Testing accuracy (%)
MLP	1 : 2	100	83.33
	1 : 1	100	84.44
	2 : 1	100	86.67
RBF	1 : 2	100	81.67
	1 : 1	100	82.22
	2 : 1	100	83.33
EP-RBF	1 : 2	100	86.67
	1 : 1	100	88.89
	2 : 1	100	93.33

time required to construct the diagnostic model using the EP-RBF network was slightly longer than that required for the other networks.

73.4 Conclusions

This paper has proposed the EP-RBF network to diagnose vibration faults of STGS. The proposed EP automatically determines the optimal parameters for the RBF network, which includes the number of neurons in the hidden layer, the centers of hidden neurons, the spread parameters, and the weights in the output layer of the RBF network. The following conclusions can be derived from this paper:

(1) The RBF network trained much faster than the MLP; however, the RBF network generally cannot quite achieve the accuracy of the MLP network.
(2) The MLP and the RBF networks trained by the gradient-based algorithm seem prone to becoming stuck in a local minimum. The proposed EP-RBF network obtains a higher diagnostic accuracy than the MLP and the RBF networks.
(3) The test results demonstrate that EP increases the diagnostic accuracy of the EP-RBF and improves the existing disadvantages of the RBF network.

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